Для цитирования: Экономика региона. — 2015. — №3. — С. 114-122
For citation: Ekonomika regiona [Economy of Region], — 2015. — №3. — pp. 114-122
doi 10.17059/2015-3-10
UDC: 314.17

G. Betti [a]***, E. Caruana*** [b]***, S. Gusman*** [b]***, L. Neri*** [a]
[a] University of Siena (Siena, Italy)
[b] National Statistics Office (Valletta, Malta)

ECONOMIC POVERTY AND INEQUALITY AT REGIONAL LEVEL IN MALTA: FOCUS ON THE SITUATION OF CHILDREN[1]

This paper performs an economic poverty and inequality mapping of three children age categories in Malta; it consists in the first attempt based on income from the EU-SILC survey and Census data. From a policy-making point of view, the availability of such key economic indicators at locality level certainly provides a valuable tool in assessing the effectiveness of national strategies and in identifying areas that need to be targeted by new policies; in fact sample surveys alone cannot provide reliable information at such a fine level of detail, while national censuses are not designed to and cannot be extended to cover specific topics such as economic poverty and inequality. Thus, the merging of the two sources provides policy-makers with a new insight into the differences between localities. There are also benefits of a technical nature, particularly in terms of sampling strategies, that can be derived from this study. Through such an exercise it is possible to identify economic homogeneity and/or heterogeneity among households with children in different localities: this is useful when defining strata for sampling design for surveys aiming at studying other economic phenomena relating to children.

Keywords: economic poverty mapping among children, Malta, sampling strategies on economic surveys

1. Introduction

Economic poverty and inequality maps are spatial descriptions of the distribution of poverty and inequality; for their construction, living standard information covering consumption expenditure are needed. Generally censuses do not collect expenditure information, so poverty estimates are not computable even in the census year. On the other hand, living standard surveys generally cover consumption, however, do not normally permit sufficiently fine disaggregation because of the limited sample size. In order to fill this gap, the World Bank has invested in a methodology for generating small area economic poverty and inequality measures, thereby permitting the construction of poverty and inequality maps. The methodology, developed by Elbers, Lanjouw and Lanjouw [1], has been applied to a substantial number of developing countries, and in many cases the results obtained have been used by governments to allocate financial resources.

The scope — and the original contribution of this paper — consists in the first attempt of implementing an economic poverty and inequality mapping based on income (instead of consumption expenditure) from the European Union — Statistical on Income and Living Conditions (EU-SILC) survey and Census data. Moreover, the attention is focussed on three age group categories of children, since they are often the most affected by economic poverty.

Statistics on children are therefore extremely important for policy makers, in order to propose ad hoc policies, to combat and eradicate problems such as famine, poverty, exclusion form education, social life, etc., and in order to monitor the effectiveness of already undertaken policies. Statistics on children are very important also in developed countries and particularly in the European Union. Information about the economic status where children live, their health status, their involvement in labour activities, their possible social exclusion, the general condition of immigrated children or children born in a EU country from immigrated parents are extremely useful information. In the former EU —15 countries, the quality of such data has reached a very high standard and the Commission has the goal to standardise and harmonise this quality level among the current EU-28, including Malta.

The basic idea is to estimate a linear regression econometric model with local variance components using the information from the smaller and richer data sample, in the Maltese SILC conducted in 2005, including some aggregate information from the Population and Housing Census or other sources available for all the statistical units in the sample. The vector of covariates utilised in the regression model should be restricted to those variables that can also be linked to households in the census.

The estimated distribution of the dependent variable in the regression model (monetary variable) can, therefore, be used to generate the distribution for any sub-population in the census conditional to the sub-population's observed characteristics. Using the estimated distribution of the monetary variable in the census data set or in any of its sub-populations, a set of economic poverty measures based on the Foster-Green-Thorbecke indexes (for $\alpha = 0,1,2$) have been computed: the Sen index and an absolute poverty line calculated using the information contained in the rich sample survey, as well as a set of inequality measures based on the Gini coefficient, the Gini coefficient of the poor and two general entropy (GE) measures, with parameter $c = 0,1$. Moreover, bootstrapping standard errors of the welfare estimates will be computed so as to assess the precision of the estimates.

This paper is made up of five sections. After this introduction, section two is devoted to the comparison and the harmonisation of the data sources, giving special attention to the Census and SILC data sets. In section three, the estimated econometric linear regression models with variance components are reported and there is a full description of how the Montecarlo simulation has been considered in order to prepare the statistical information for calculating bootstrapping standard errors of poverty and inequality measures. Section four reports the above-described indices calculated for the whole children population of Malta and disaggregated at district and locality levels; three age-groups of children have been identified, according to the education system: 0–5, 6–13 and 14–17 years. Finally, section five reports concluding remarks and recommendations; in fact, from a policy-making point of view, the availability of economic key indicators at locality level certainly provides a valuable tool in assessing the effectiveness of national strategies and in identifying areas that need to be targeted by new policies on economic phenomena.

2. Data sources

Malta is geographically divided into two Regions, Malta and Gozo-Comino. These are divided into 6 Districts which, in turn, are divided into 68 Localities.

The two main sources of statistical information available in Malta are: The Population and Housing Census (PHC) — 2005, and The Statistics on Income and Living Conditions (SILC) survey — 2005.

The 2005 Population and Housing Census was undertaken between 21st November 2005 and 11th December 2005, with the midnight of 17th November 2005 as reference time of the census [2]. This was the sixteenth census being carried out since the first one that was undertaken in 1842, and was carried out in terms of the Malta Census Act of 1948. The target population of the Population and Housing Census included all persons (nationals and non-nationals) as well as all households that were residing in Malta and Gozo as on the census night. Moreover, detailed information was collected on main and secondary dwellings, as well as on vacant ones. The enumerated total population stood at 404,962 persons. The total count of private households stood at 139,583. Nearly 19 percent of these households were single-member households, while two- and three-person households amounted to 26 and 22 percent of the total number of private households respectively. The average household size stood at 2.9. The region of Gozo and Comino (NUTS 3 classification divides Malta into two regions namely, Malta and Gozo and Comino) turned out to be the smallest amongst the six districts in Malta (according to NUTS 4 classification). In fact, this region comprised only 10,744 or 8 percent of the total household population. On the other hand, the Northern Harbour district stood out as the largest district in Malta with a total of 42,731 private households (31 percent), while the Southern Harbour region came next with 28,192 households living in this district.

The census questionnaire contained many questions that have been collected in EU-SILC since the first data collection, in 2005. Information common to these two surveys includes household size, household type, the number of rooms in main dwelling, tenure status, availability of various household amenities, labour status and occupation of a head of a household person. These data were collected in the census according to UNECE recommendations and were also in line with EU-SILC definitions and methodological recommendations, which was the key for the success of the poverty mapping project.

The Statistics on Income and Living Conditions survey is an annual survey carried out simultaneously by all EU member states. It is a rich source of statistics on income distribution and aims to provide a complete set of indicators on poverty, social exclusion, pensions and material deprivation. This project is coordinated by Eurostat to ensure harmonised definitions and methodologies, and consequently comparability across all EU member state countries. In Malta, EU-SILC was conducted by the National Statistics Office (NSO), for the first time in 2005. The fact that this is an annual survey makes possible, not only to depict the situation on poverty and social exclusion in Malta at a specific point in time, but also to monitor changes in living conditions over time.

The method used for EU-SILC data collection involves personal interviews. The target population consists of all persons residing in private households in Malta at the time of data collection. In EU-SILC 2005, a sample of 5,104 households was selected through simple random sampling of dwellings from the Water Services database, which served as the sampling frame for the survey [3]. This sample yielded a total of 4,709 eligible households that were approached for an interview. Of these, 3,459 households responded to the survey such that information on a personal level was collected for a total of 10,282 persons (of whom 8,246 were aged 16 and over).

The main indicators that are derived from EU-SILC are based on household income which is collected, component by component, at the individual level. When averaged over all household members through the use of an appropriate equivalence scale, the household income provides a reliable indication of the monetary well-being of the households. This is also the basis for the calculation of the at-risk-of-poverty rate, which is one of the most important EU-SILC indicators. Various disaggregations of these indicators make possible to shed light on which population categories are most prone to poverty. Simultaneously, EU-SILC collects other information related to topics such as health and disability, employment, education and material deprivation.

The two sources of data have been fully analysed in order to identify the common concept and to construct the common variable to be compared. The original Census and SILC variables have been transformed in order to get comparable variables, divided into three categories:

a) household dwelling conditions and presence of durable goods,

b) household head characteristics,

c) household socio-demographic characteristics.

Each one of the 31 variable distributions from the Census was compared with the corresponding weighted distribution from the SILC, and a chi-square test was used for the comparisons.

3. Poverty mapping for small area estimation of income-based indicators

The basic idea can be explained in a simple way. Having data from a smaller and a richer data-sample such as a sample survey and a census, a regression model of the target household-level variable, given a set of covariates based on the smaller sample, can be estimated. Restricting the set of covariates to those that can also be linked to households in the larger data source, the estimated distribution can be used to generate the distribution of the equivalised income (y_h) for the population or sub-population in the larger sample given the observed characteristics. Therefore, the conditional distribution of a set of welfare measures can be generated and the relative point estimates and standard errors can be calculated.

Practically the methodology follows two stages:

a) the survey data are used to estimate a prediction model for the income

b) simulation of the income for each household of the census in order to compute poverty/inequality measures with their relative prediction error.

As regard to the empirical analysis introduced in this paper, the survey-based regression model is based on SILC survey, the prediction at the household level are based on the entire Census data.

Stage one consists in developing an accurate empirical model of a logarithmic transformation of the total household equivalised income, measured in Maltese Lira (Lm) during the reference year 2004. The survey-based regression model developed for income is critical in order to obtain accurate poverty statistics. Denoting by $\ln y_{ch}$ the logarithm equivalised income of household h in cluster c, a linear approximation to the conditional distribution of $\ln y_{ch}$ is considered:

$$\ln y_{ch} = E\left[\ln y_{ch} \mid x_{ch}^T\right] + u_{ch} = x_{ch}^T \beta + u_{ch}. \qquad [1]$$

Previous experience with survey analysis [1, 4] suggests that the proper model to be specified has a complex error structure, in order to allow for a within-cluster correlation in the disturbances as well as heteroscedasticity. To allow for a within cluster correlation in disturbances, the error component is specified as follows:

$$u_{ch} = \eta_c + \varepsilon_{ch}, \qquad [2]$$

where η and ε are independent of each other and not correlated to the matrix of explanatory variables. Since residual location effects can highly reduce the precision of welfare measure estimates, it is important to introduce some explanatory variables in the set of covariates which explain the variation in income due to location. For this reason, introducing locality-level explanatory variables among the explanatory variables of the model is crucial. Such variables can be recovered from external datasets and/or from census data. In the empirical analysis presented, the locality-level explanatory variables are computed as average, over all the census households in the 68 Localities, of the introduced covariates.

Some preliminary analyses on the Maltese SILC suggest that the equivalised income is locally different so, in order to avoid forcing the parameter estimates to be the same for the whole country, it has been decided to estimate separate regression models for the following areas:

— Southern Harbour and South Eastern (Districts 1 and 3)

— Northern Harbour (District 2)

— Western and Northern (Districts 4 and 5)

— Gozo and Comino (District 6)

Geographical differences in the level of prices are taken into account (SILC variable *eq_inc_lm*). From the fitting of model [1], the residual can be computed and used as estimates of the overall disturbances of $\hat{u}_{ch}$. This residual is decomposed into uncorrelated household and location components as follows: $\hat{u}_{ch} = \hat{\eta}_{ch} + e_{ch}$. The estimated location components ($\hat{\eta}_c$) are the within cluster means of the overall residual. The household component estimates (e_{ch}) are the overall residual net of location components, these values can be used to estimate the variance of ε_{ch}.

To allow for heteroscedasticity in the household component, a model is chosen which explains its variation best. The covariates of this model can be the usual covariates as well as their squares or interactions between variables, the chosen set is labelled with z. A logistic model of the variance ε_{ch} conditional on z is estimated (bounding the prediction between zero and a maximum A equal to $1.05\times\max(e_{ch})$:

$$\ln\left[\frac{e_{ch}^2}{A-e_{ch}^2}\right] = z'_{ch}\,\alpha + r_{ch}.$$

Let $\exp(z'_{ch}\alpha) = B$ and using the delta method the household specific variance is estimated as:

$$\hat{\sigma}_{ch}^2 = \left[\frac{AB}{1+B}\right] + \frac{1}{2}\operatorname{var}(r)\left[\frac{AB(1-B)}{(1+B)^3}\right].$$

The variance of σ_η^2 is estimated non-parametrically, allowing for heteroscedasticity in ε_{ch} [see Appendix 2, 5]. The two variance components are combined in order to calculate the estimated variance-covariance matrix ($\hat{\Sigma}$) of the overall residual of the original model. Once $\hat{\Sigma}$ is calculated the original model can be estimated by GLS, the results are in Table 1. In the present analysis, the models for heteroscedasticity have had an R2 around 0.04, so the heteroscedasticity can be considered negligible.

Several models have been estimated for the four areas using variables shared by survey and census plus the aggregated area based variables from the census and just one local level variable in just one area is significant (see Table 1 for the regression results).

The consequent stage involves prediction at the household level based on the entire census data and aggregation to small area level. Now, the key assumption is that the models estimated from the survey data apply to census observations.

The parameter estimates obtained from the previous step are applied to the census data so as to simulate the income for each household in the census. A set of 100 simulations has been conducted. For each simulation a set of the first stage parameters has been drawn from their corresponding distribution simulated at the first stage: the beta coefficients $\tilde{\beta}$, are drawn from a multivariate normal distribution with mean $\hat{\beta}$ (the coefficients of the GLS estimation) and variance-covariance matrix equal to the one associated to $\hat{\beta}$. Relating the simulation of the residual terms $\hat{\eta}_c$ and e_{ch} any specific distributional form assumption has been avoided by drawing directly from the estimated residuals: for each cluster the residual drawn is $\tilde{\eta}_c$ and for each household $\tilde{\varepsilon}_{ch}$. The simulated values are based on both the predicted logarithm of income $x'_{ch}\tilde{\beta}$, and on the disturbance terms $\tilde{\eta}_c$ and $\tilde{\varepsilon}_{ch}$ using bootstrapped methods:

$$\ln \hat{y}_{ch} = \exp\left(x_{ch}^T\tilde{\beta} + \tilde{\eta}_c + \tilde{\varepsilon}_{ch}\right). \quad [3]$$

The full set of simulated $\hat{y}_{ch}$ is used to calculate the expected value of each of the poverty measures considered.

For each of the simulated equivalised income distributions a set of small area poverty and inequality measures has been calculated by averaging the simulated equivalised income for each small area and the variance computed over all the 100 simulations gives the standard errors for each small area. As regard to the results, in the next section are reported poverty and inequality measures calculated at the local level for children aged 0–5, 6–13 and 14–17 years.

As usual, in each poverty mapping analysis, we compare figures obtained from the sample survey estimation and from the census for the whole country.

Income figures from the SILC and the census for the whole country show some discrepancies: particularly, the at-risk-of-poverty rate based on SILC is 13.84, the one based on census is 15.33; looking at the average equivalised incomes, the one based on SILC is Lm 3,797, the one based on census is Lm 3,751.

Table 1

Regression results by District: GLS estimates for fixed effects and standard error (in parentheses)

	Districts 1&3	District 2	Districts 4&5	District 6 (Gozo)
Number_rooms	0.035*** (0.010)	0.032*** (0.010)	0.027** (0.011)	
Television			–0.256* (0.151)	
Washing_machine		0.311*** (0.068)	0.190* (0.106)	
H_type_5	0.223*** (0.041)	0.188*** (0.043)	0.288*** (0.056)	0.240*** (0.074)
H_type_7	0.416*** (0.039)	0.278*** (0.045)	0.464*** (0.050)	0.274*** (0.068)
H_type_9			0.110** (0.055)	
Ref_person_economic_activity_1			0.391*** (0.052)	
Ref_person_marital_status_2			–0.148*** (0.043)	
Ref_person_health_problem	–0.078** (0.033)	–0.101*** (0.036)		
Ref_person_education_3	0.130*** (0.048)	0.082* (0.047)	0.223*** (0.046)	
Ref_person_education_4	0.331*** (0.089)	0.192*** (0.068)	0.490*** (0.054)	
Ref_person_age		–0.014** (0.007)	0.005*** (0.002)	
Ref_person_age2		0.000** (0.000)		
Ref_person_ISCO_1	0.335*** (0.087)	0.333*** (0.056)		0.348*** (0.114)
Ref_person_ISCO_2	0.161 (0.100)	0.252*** (0.083)		0.460*** (0.123)
Ref_person_ISCO_3	0.256*** (0.057)	0.247*** (0.064)		0.309*** (0.109)
RATE_UNEMP_LT_0_25	0.319*** (0.053)	0.352*** (0.057)	0.372*** (0.087)	0.394*** (0.108)
RATE_INACT_LT_0_25		0.276*** (0.034)		0.402*** (0.052)
RATE_RET_LT_0_5	0.146*** (0.037)	0.227*** (0.048)	0.125** (0.054)	0.385*** (0.055)
Males_50_59		0.155*** (0.042)		
Females_30_39			–0.106** (0.046)	
Females_50_59			–0.071 (0.044)	
m_DWELLING_TYPE_1_2	–0.326** (0.145)			
Random effect	**			

* denotes significance at the 10 % level, ** at the 5 % level, and *** at the 1 % level.

The discrepancies can be related to a possible bias which can affect estimators based on poverty mapping if there are no area-specific predictors to control area specific bias. Demombynes et al. [6] demonstrated that ELL performance depends on the locality-level explanatory variables inserted into the income model based on survey data. In our empirical analysis, there was not external information to create variable able to incorporate in the model contextual effect, and unfortunately, the variables computed as average cluster level on census data are not significant in the specified models. However, in the case of Malta, regional estimates based on direct or small area estimation cannot be computed, and the ELL is the only methodology which could be applied [7]. Being based on a regression model function of a set of diverse type of independent variables, ELL could be seen a sort of multidimensional approach to poverty analysis. Among others, the most important papers describing multidimensional approaches could be Atkinson and Bourguignon [8], Tsui [9], Maasoumi [10], Anand and Sen [11], Sen [12], Duclos, Sahn and Younger [13], Atkinson et al. [14], Atkinson [15], Alkire and Foster [16]; one of the most popular multidimensional approach presented in literature is the one based on fuzzy set theory [17-23].

4. Poverty and inequality measures for children

Table 2 reports poverty and inequality measures calculated for the six Districts for children aged 0–5, 6–13 and 14–17 years. Figures 1, 2 and 3 report the percentage of children at-risk-of-poverty aged 0–5, 6–13 and 14–17 years among the 68 municipalities. The at-risk-of-poverty rates amongst children increased with increasing age. As an example, the at-risk-of-poverty rate among children within Gozo and Comino increased from 15.9 percent among children aged under 6 to nearly 20 percent within the 14–17 year old age group. This may be explained due to the fact that many households with children aged over 5 tend to have more than one child and less work intensity. Consequently, the equivalised income for these households tends to be lower than the other households with a resulting increase in the at-risk-of-poverty rate.

Through this exercise, it is also interesting to observe how the at-risk-of-poverty rates for children in certain localities differ significantly from that estimated for neighbouring localities. For example, if we focus on the 0–5 age-group, localities that stand out in particular in this respect are Marsascala in the South Eastern district, Fgura in the Southern Harbour district, Mtarfa and Attard

Table 2

Poverty and inequality indices (%) for children

Age group	District	Head count	FGT(1)	FGT(2)	Gini	Gini-poor	Sen	GE(0)	GE(1)	Eq_inc_lm*
0-5	Malta	16.31	4.09	1.76	27.80	15.02	3.02	13.72	12.92	3,588
	District_1	18.06	4.20	1.70	25.97	13.57	3.12	11.96	11.22	3,313
	District_2	14.10	3.62	1.60	28.23	15.69	2.64	14.10	13.39	3,788
	District_3	16.68	3.88	1.59	26.67	13.74	2.87	12.55	11.81	3,469
	District_4	16.79	4.52	2.02	28.24	16.11	3.36	14.30	13.22	3,647
	District_5	17.25	4.54	2.00	27.95	15.65	3.38	13.98	12.95	3,586
	District_6	15.91	4.10	1.85	29.07	15.91	3.08	15.19	14.30	3,728
6-13	Malta	17.30	4.31	1.84	27.55	14.88	3.21	13.50	12.73	3,485
	District_1	18.34	4.27	1.73	26.01	13.60	3.19	12.02	11.26	3,301
	District_2	14.87	3.77	1.65	28.03	15.41	2.77	13.90	13.26	3,685
	District_3	17.70	4.13	1.68	26.35	13.68	3.07	12.30	11.54	3,372
	District_4	17.94	4.73	2.08	27.91	15.70	3.55	13.95	12.96	3,505
	District_5	18.92	4.99	2.18	27.60	15.62	3.77	13.69	12.67	3,424
	District_6	17.79	4.47	1.97	28.75	15.31	3.41	14.80	14.10	3,538
14-17	Malta	17.15	4.29	1.84	27.52	14.92	3.19	13.49	12.69	3,495
	District_1	18.31	4.31	1.75	26.46	13.71	3.20	12.42	11.66	3,342
	District_2	15.03	3.80	1.65	27.48	15.32	2.79	13.41	12.75	3,626
	District_3	18.42	4.34	1.77	26.80	13.72	3.24	12.70	11.95	3,369
	District_4	17.20	4.56	2.01	28.29	15.78	3.39	14.31	13.31	3,605
	District_5	16.98	4.50	2.01	27.75	15.92	3.37	13.86	12.82	3,563
	District_6	19.83	5.01	2.20	27.59	15.39	3.90	13.87	13.10	3,293

* Eq_inc_lm stands for equivalised income (Maltese liras).

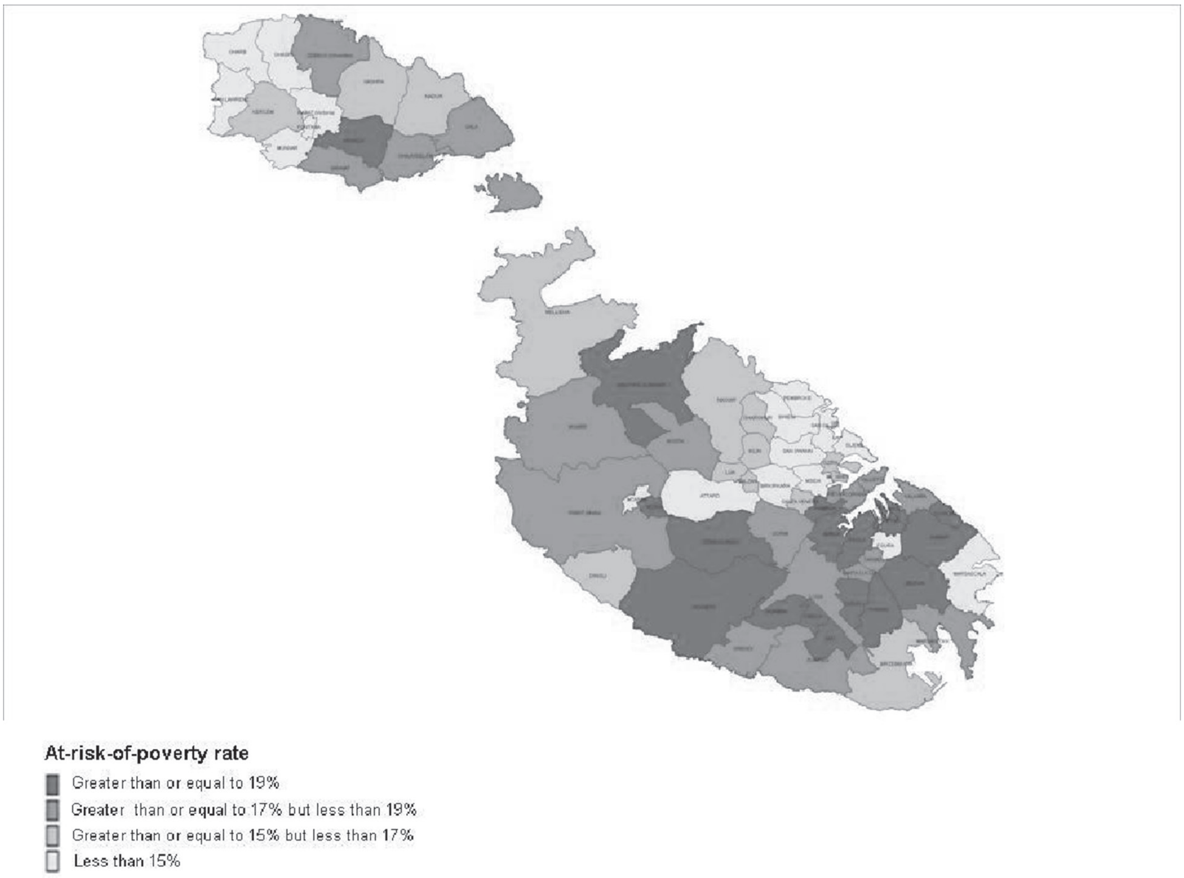

Fig. 1. *HCR children aged 0–5 by Localities*

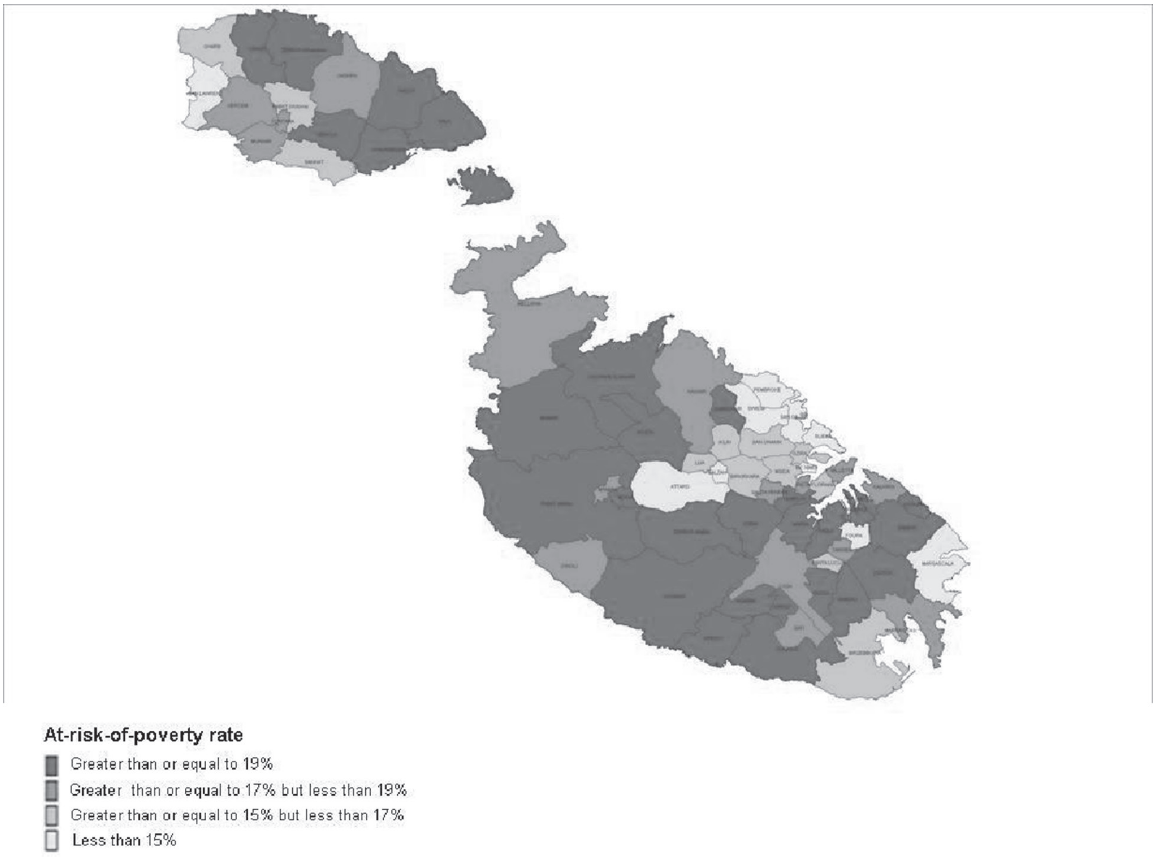

Fig. 2. *HCR children aged 6–13 by Localities*

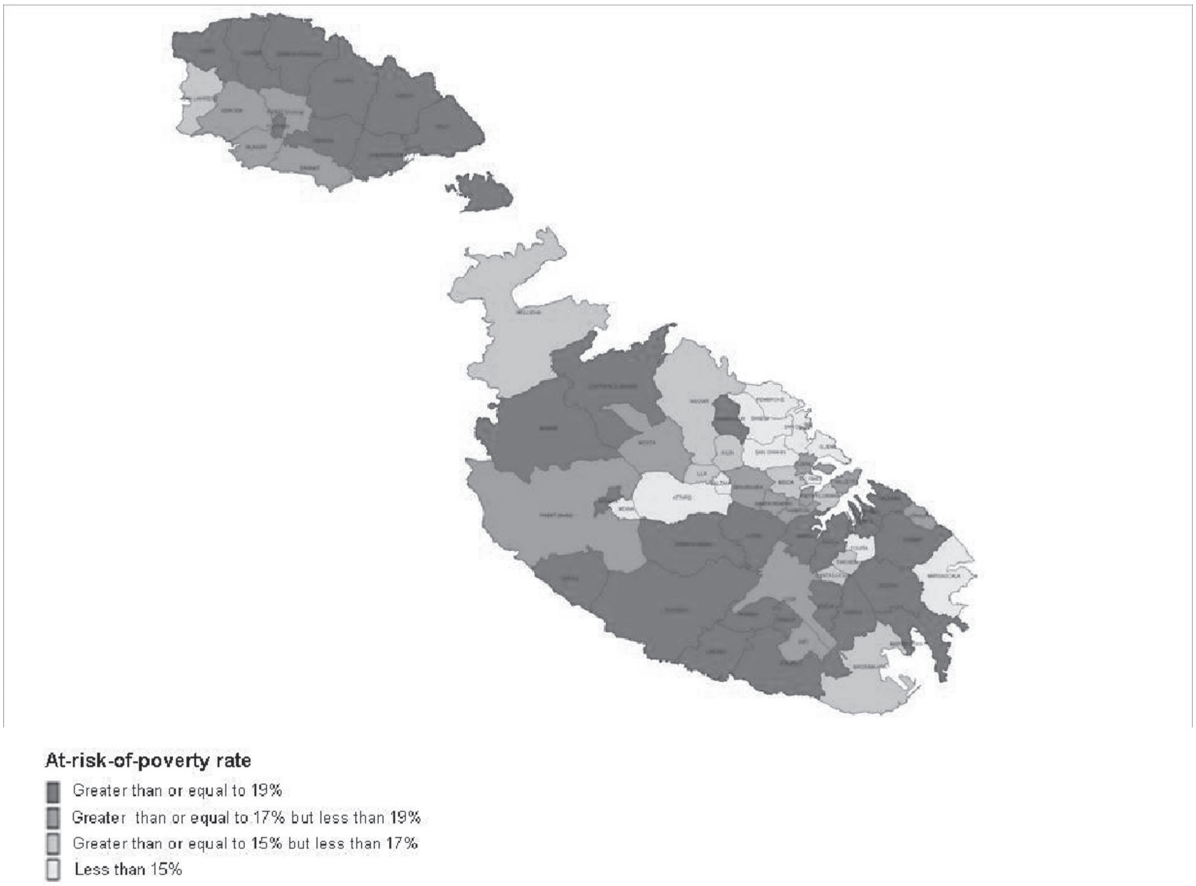

Fig. 3. *HCR children aged 14–17 by Localities*

in the Western district. The at-risk-of-poverty rate for children aged between 0 and 5 was estimated to be less than 15 % in these localities, which is in contrast with neighbouring localities. At the other end of the scale, St. Paul's Bay in the Northern district stands out for having a relatively high at-risk-of-poverty rate among young children when compared to other localities in the vicinity.

In general, children are considered to be a vulnerable group. The at-risk-of-poverty rate for persons aged between 0 and 17 is, in fact, higher than that estimated for the population as a whole. However when analysing results at locality level, it can be observed that for certain localities the opposite is true. This is the case in 18 localities for the 0–5 age-group, 10 localities in the 6–13 age group and 6 localities in the 14–17 age groups.

5. Conclusions and recommendations

The results derived from this study are of interest in their own right, but furthermore they can be applied advantageously within different fields, as will be described below.

From a policy-making point of view, the availability of key indicators at locality level (LAU2) certainly provides a valuable tool in assessing the effectiveness of national strategies and in identifying areas that need to be targeted by new economic policies, moreover the map representation convey an enormous amount of information about the spread and relative magnitude of poverty across localities, in a way which is quickly and intuitively absorbed also by non-technical audiences. Such detailed geographical profiles of poverty and inequality across a country are valuable inputs for a wide variety of debates and deliberations, amongst policymakers as well as civil society.

There are also benefits of a technical nature, particularly in terms of sampling strategies for survey studying any economic phenomena that can be derived from this study. Through such an exercise, it is possible to identify economic homogeneity and/or heterogeneity among households in different localities (and potentially in even smaller units within these localities). This is useful when defining strata for stratification sampling in any economic survey. For example generally, in stratified sampling, a group of neighbouring localities belonging to the same district are grouped into one stratum. However, this study has shown how it may be wise to rethink such stratification, since certain localities in the same district have come across as having very contrasting realities in terms of economic poverty. Similarly, this study would be useful to determine efficient cluster sampling. The clusters are assumed to be homogeneous such that the sampling variance of the estimators depends on the variation between the clusters and not within them. This study can shed some light on how safe it is to make these assumptions.

One further important advantage of this study is that it can be extended from a national project into one at the European level. The structures for this are already in place through the availability of 2011 census data for most countries and the existence of a number of harmonised surveys such as that on Statistics on Income and Living Conditions (EU-SILC), Household Budget Surveys (HBS) and the Labour Force Survey (LFS). As a result, the methods used in this study may be applied to most European countries in order to estimate various key economic indicators, thus maximising the output of these important surveys.

References

1. Elbers, C., Lanjouw, J. O. & Lanjouw, P. (2003). Micro-level Estimation of Poverty and Inequality. *Econometrica, 71,* 335-364.

2. NSO. (2007, July). Census of Population and Housing 2005.

3. NSO. (2006, December). EU-SILC 2005 Final Quality Report.

4. Neri, L., Ballini, F. & Betti, G. (2005). Poverty and inequality mapping in transition countries. *Statistics in Transition, 7(1),* 135-157.

5. Elbers, C., Lanjouw, J. O. & Lanjouw, P. (2002). Micro-level Estimation of Welfare. *Working Paper No 2911.* The World Bank, Washington, D.C.

6. Demombynes, G., Lanjouw, J. O., Lanjouw, P. & Elbers, C. (2006). How good a map? Putting Small Area Estimation to the Test. *Policy Research Working Paper No. 40155.* The World Bank.

7. Betti, G., Gagliardi, F., Lemmi, A. & Verma, V. (2012). Sub-national indicators of poverty and deprivation in Europe: methodology and applications. *Cambridge Journal of Regions, Economy and Society, 5(1),* 149-162.

8. Atkinson, A. B. & Bourguignon, F. (1982). The comparison of multidimensional distributions of economic status. *Review of Economic Studies, 49,* 183-201.

9. Tsui, K. (1985). Multidimensional generalisation of the relative and absolute inequality indices: the Atkinson-Kolm-Sen approach. *Journal of Economic Theory, 67,* 251-265.

10. Maasoumi, E. (1986). The measurement and decomposition of multidimensional inequality. *Econometrica, 54,* 771-779.

11. Anand, S. & Sen, A. K. (1997), *Concepts of human development and poverty: a multidimensional perspective.* Human Development Papers, United Nations Development Programme (UNDP), New York.

12. Sen, A. K. (1999). *Development as freedom.* Oxford University Press, Oxford.

13. Duclos, J.-Y., Sahn, D. & Younger, S. D. (2001). *Robust multidimensional poverty comparisons.* Canada: Université Laval.

14. Atkinson, A. B., Cantillon, B., Marlier, E. & Nolan, B. (2002). *Social Indicators: The EU and Social Inclusion.* Oxford: Oxford University Press.

15. Atkinson, A. B. (2003). Multidimensional deprivation: contrasting social welfare and counting approaches. *Journal of Economic Inequality, 1,* 51-65.

16. Alkire, S. & Foster, J. (2011). Counting and multidimensional poverty measurement. *Journal of Public Economics, 95(7-8),* 476-487.

17. Cerioli, A. & Zani, S. (1990). A fuzzy approach to the measurement of poverty. In: Dagum C. and Zenga M. (Eds). *Income and wealth distribution, inequality and poverty.* Berlin: Springer Verlag, 272-284.

18. Cheli, B. & Lemmi, A. (1995). A Totally Fuzzy and Relative Approach to the Multidimensional Analysis of Poverty. *Economic Notes, 24,* 115-134.

19. Cheli, B. & Betti, G. (1999). Fuzzy analysis of poverty dynamics on an Italian pseudo panel, 1985-1994. *Metron, 57,* 83-104.

20. Betti, G., Cheli, B. & Cambini, R. (2004). A statistical model for the dynamics between two fuzzy states: theory and application to poverty analysis, *Metron, 62(3),* 391-411.

21. Belhadj, B. (2011). A new fuzzy unidimensional poverty index from an information theory perspective. *Empirical Economics, 40(3),* 687-704.

22. Belhadj, B. (2012). New weighting scheme for the dimensions in multidimensional poverty indices. *Economic Letters, 116(3),* 304-307.

23. Belhadj, B. & Limam, M. (2012). Unidimensional and multidimensional fuzzy poverty measures: New approach. *Economic Modelling, 29(4),* 995-1002.

Authors

Gianni Betti — PhD in Applied Statistic, Associate Professor, Department of Statistics and Economics, University of Siena (7, Piazza S. Francesco, Siena, 53100, Italy; e-mail: Gianni.betti@unisi.it).

Etienne Caruana — MSc in Statistics & Operations Research, Director of Social Statistics, National Statistics Office (Lascaris, Valletta VLT 2000, Malta; e-mail: carue006@gmail.com).

Sarah Gusman — MSc in Statistics, Principal Statistician, National Statistics Office (Lascaris, Valletta, Malta; e-mail: gusman.sarah@gmail.com).

Laura Neri — PhD in Applied Statistic, Assistant Professor in Statistics and Economics, Department of Economics and Statistics, University of Siena (7, Piazza S. Francesco, Siena, 53100, Italy; e-mail: laura.neri@unisi.it).